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IQ level prediction and cross-relational analysis with perceptual ability using EEG-based SVM classification model

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ABSTRACT

This paper presents IQ level prediction and cross-relational analysis with perceptual ability using EEG-based SVM classification model. The study hypothesized that measure of perceptual ability and intelligence is strongly connected through the brain's attention regulatory mechanism. Therefore, an intelligent classification model should be able to predict and map IQ levels from a dataset associated with varying levels of perception. 115 samples of resting EEG is acquired from the left prefrontal cortex. Sixty-five is used for perceptual ability analysis via CTMT, while another fifty is used in the development of IQ level classification model using SVM. The mean pattern of theta, alpha and beta bands show positive correlation between perceptual ability and IQ level datasets. Meanwhile, the developed SVM model outperforms the previous ANN method; yielding 100% accuracy for training and testing. Subsequently, the classification model successfully predicts and mapped samples from the perceptual ability dataset to its corresponding IQ levels with 98.5% accuracy. Therefore, validity of the study is confirmed through positive correlation demonstrated by both traits of cognition using the pattern of mean power ratio features, and successful prediction of IQ level for perceptual ability dataset via SVM classification model.

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1. INTRODUCTION

The measure of perception [1] and intelligence [2] are among the established mental constructs in the domain of psychology. Generally, perception is defined the as the ability of individuals to interpret and process sensory information from the surrounding environment [3]. This can be assessed using Comprehensive Trail-Making Test (CTMT) [4]. The ability is strongly associated with attentional state [5] and its signatures can be observed through the alpha band [6]. Hence, the strength of neural synchronization commonly observed in resting state can be used to predict the level of perception [7]. Conversely, the measure of intelligence is associated with efficiency of the brain to process information [8]. Intelligence quotient (IQ); an established parameter to assess this mental construct are assessable through Raven's Progressive Matrices (RPM) [9]. Evidences have shown that perception and intelligence are strongly associated through mechanism that regulates attention [10]. Studies have also established that intelligent individuals exhibit well-functioning neurotransmitters which result in smaller deviation of rhythmic EEG [11]. The lower cerebral arousability is attributed by inhibition of brainstem to external excitation [12]. These reduce cortical noise and subsequently, enhance attentional state [13] and response time [14]. The increased alpha power, approximately around 10 Hz enables the brainstem to block task-irrelevant cortical activities and thus, maintaining attentional state [15]. These further translate into increased perceptual limits and enhance the level of perception [16]. Alpha band shares a reciprocal with oscillations in both theta [17] and beta regions [18]. Hence, increased synchronization in the alpha region desynchronizes theta and beta oscillations. By associating both cognitive traits through the attentional state, a positive correlation can be observed. Therefore, high level of perception is expected in individuals with high IQ, and vice versa. These however, have yet to be confirmed through valid experimental protocols.

Brain behavior can be observed through the electroencephalogram (EEG). Past studies have studies have demonstrated that the resting EEG from left prefrontal cortex is capable of predicting various traits of cognition such as intelligence [19-20], learning styles [21-22] and perceptual ability [4]. An intelligent IQ level classification model has been previously established using artificial neural network (ANN). Although yielding excellent training accuracy, its performance during testing has indicated over-fitting problems. These are attributed by the absence of early-stopping criterion that ensures optimum generalization ability of the ANN [19]. The classification model however, can still be improved using superior techniques such as support vector machine (SVM). Among the main advantages of such method is its ability to attain good generalization ability, even with small sample size [23]. The following are issues that shall be the focus of this study. First, the relationship between perceptual ability and intelligence has yet to be addressed through EEG observations. Second, the established IQ level classification model has demonstrated limitations that could be overcome using SVM. Third, a cross-relational mapping between both traits of cognition has yet to be established through a computational model. Consequently, the following objectives have been outlined; 1) to characterize mean pattern of theta, alpha and beta ratio features for different levels of perceptual ability, 2) to develop an IQ level classification model using SVM, and 3) to implement the established model for predicting IQ levels from the perceptual ability dataset. The outcomes are expected to validate prior assumptions that both traits of cognition are positively correlated.

2. RESEARCH METHOD

The study comprises of data acquisition, signal pre-processing and feature extraction, and analysis of mean power ratio pattern for the respective levels of perceptual ability. These are followed by the development of IQ level classification model using SVM, and IQ level prediction from perceptual ability dataset. The general framework of research methods is shown in Figure 1.

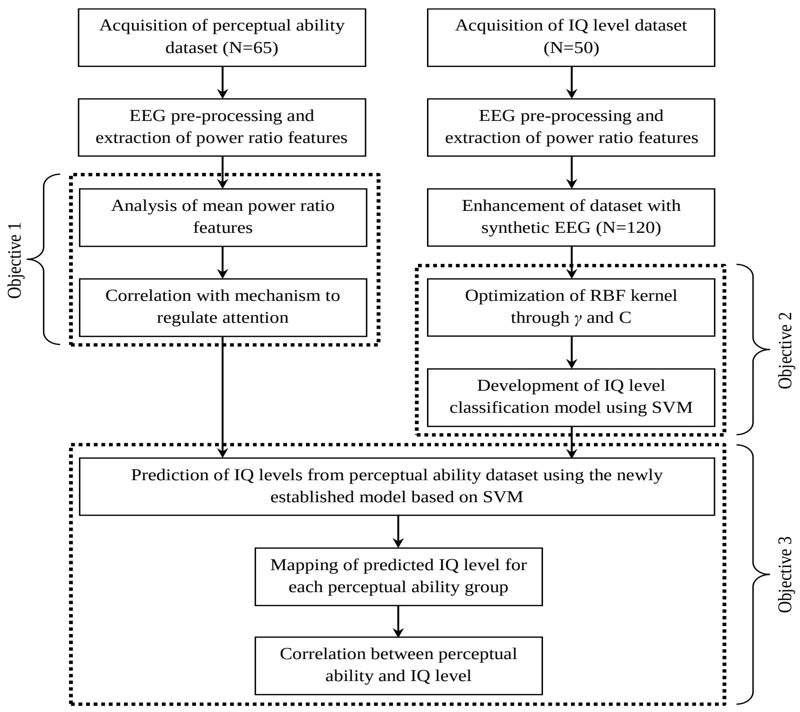


Figure 1. General research framework

2.1. Data acquisition, EEG pre-processing and feature extraction

A total of 65 healthy subjects have participated in the study (right-handed, age range = 20–40 years, mean age = 27.1 years, standard deviation = ±4.4 years). Written consent is obtained prior to data collection. All protocol has received approval from the university's Research Ethics Committee (600-IRMI (5/1/6)). Subjects are required to complete five trails of the CTMT. Subsequently, resting EEG is acquired from the left prefrontal cortex using NeuroSky Mindwave Mobile during which, participants are required to relax with both eyes closed. The recording spans approximately 3 minutes. The T-score from CTMT is used to establish the high, medium and low perceptual ability groups [4]. The EEG is pre-processed for noise removal and electrooculogram rejection. 150 seconds segment is retained and filtered into theta, alpha and beta waves [24]. Power spectral density (PSD) is determined using Fast Fourier Transform and Welch method [19]. Energy spectral density (ESD) is then extracted as the area under PSD curve per unit frequency [24]. The information is further normalized via (1), (2) and (3) where θ, α and β each represents the ESD in theta, alpha and beta bands. The tasks are performed in MATLAB environment.

$$\text{Theta Ratio} = \frac{\theta}{\theta+\alpha+\beta} \tag{1}$$

$$\text{Alpha Ratio} = \frac{\alpha}{\theta+\alpha+\beta} \tag{2}$$

$$\text{Beta Ratio} = \frac{\beta}{\theta+\alpha+\beta} \tag{3}$$

2.2. Development of IQ level classification model using support vector machine

SVM is implemented in the IQ level classification model. The model is developed based on fifty samples acquired from the preceding study. Additional seventy samples of synthetic EEG were also used to enforce the model. Three control groups were previously established via RPM; high, medium and low IQ groups [19]. Hence, error-correcting output codes are implemented for the multi-class SVM model. Through non-linear mapping, data is initially mapped to high dimensional space. Subsequently, linear classification is performed through (4) where $f(x)$ is the classification function, w is weight vector of hyper-plane coefficients, and b is the bias.

$$f(x) = wx + b \tag{4}$$

A radial basis function (RBF) kernel is used due to its stability. RBF on samples x and x' are feature vectors in an input space and is expressed by (5) where γ is a parameter that defines the influence of training samples. Another parameter to control generalization ability of SVM is the box constraint, C. It controls the maximum penalty imposed on margin-violating observations and aids in preventing over-fitting [23].

$$K(x, x') = \exp\left(-\gamma\|x - x'\|^2\right) \tag{5}$$

The theta, alpha and beta ratio features are used is input to train and test the SVM. 5-fold cross-validation is also implemented in the development of the model. The randomly segregated for training and testing with 80:20 split ratio. Subsequently, the developed model is used to predict IQ level groups from the previously established perceptual ability dataset. The mapping of samples between two datasets will validate the expected relationship between both intelligence and perception. Accuracy for both training testing is described by (6) where TP, TN, FP and FN each represents the true positive, true negative, false positive and false negative.

$$Acc = \left(\frac{TP+TN}{TP+TN+FP+FN}\right)\times 100\% \tag{6}$$

3. RESULTS AND DISCUSSION

3.1. Analysis of mean power ratio features for different levels of perceptual ability

Three distinct levels of perceptual ability are determined based on the T-scores of CTMT. The distribution of samples is based on qualitative descriptions in the manual booklet. Seven samples are categorized as low level, forty-five samples as medium level and the remaining thirteen samples as high level of perception. Subsequently, the obtained theta, alpha and beta ratio features are clustered into the three levels of perceptual ability. Table 1 shows the mean power ratio features for each level of perception. A qualitative description is also provided on its trending pattern with increasing level of perception. The mean power ratio features show conformity with previous study where both theta and beta ratio demonstrates a decreasing trend. Conversely, the pattern of alpha ratio indicated an increasing trend.

The highest mean theta ratio attained by low perceptual ability group demonstrates relatively poorer efficiency in blocking task-irrelevant cortical activities, thus increasing cortical noise which resulted in reduced attentional state. Furthermore, these also reflect somewhat less efficient functioning of neurotransmitters. Thus, these increase the probability of neurons firing transmission errors [13]. Conversely, the highest mean alpha ratio is obtained by those with high level of perception; reflecting increased synchronization of alpha oscillations. These desynchronize both theta [25] and beta [18] waves; resulting in lowest mean for those EEG bands. The increased oscillation around 10 Hz enables the brainstem to block task-irrelevant cortical activities [15] which aids in sustaining attention [6]. The high level of perception is also attributed to lower cortical noise from efficient functioning neurotransmitters [16]. Generally, a positive correlation has been observed between perceptual ability and attentional state [5-6, 16]. The observed power ratio pattern also indicated conformity with the Neural Efficiency Hypothesis of human intelligence [6, 8]. Alpha ratio has shown increasing trend from low to high IQ level. Conversely, theta and beta ratio has demonstrated decreasing trend to that of alpha ratio [24]. The observed pattern in the three EEG bands is explained through underlying mechanisms that regulate attention. It is strongly associated with the neural transmission error and alpha suppression theories that result in increased level of attention; resulting in optimized brain capacity [15], heightened perceptual limits and response time [7]. Thus as summarized by Table 2, a positive correlation between the two traits of cognition can be observed.

Table 1. Mean power ratio and pattern description with increasing level of perception

Power Ratio	Level of Perceptual Ability Low	Medium	High	Pattern Description with Increasing Level of Perception
Theta	0.4246	0.3942	0.3344	Decreasing
Alpha	0.4645	0.5060	0.5567	Increasing
Beta	0.1127	0.1107	0.1090	Decreasing

Table 2. Pattern of power ratio features with increasing levels of perceptual ability and IQ

Power Ratio Features	Increasing Level of Perception	Increasing Level of IQ
Theta	Decreasing	Decreasing
Alpha	Increasing	Increasing
Beta	Decreasing	Decreasing

3.2. Development of IQ level classification model using SVM

The RBF kernel is initially optimized with parameters γ and C is set at 1000 and 0.001, respectively. As a result, the SVM has shown marked improvement from the one previously developed using ANN [26]. Training and testing of the IQ level classification model yielded 100% accuracy. Thus, the hyper-planes are able to cleanly separate the power ratio features among the established control groups. In contrast, the previous ANN model was only able to attain testing accuracy of 88.9%. Table 3 shows the comparison between both approaches.

Table 3. Performance comparison between the proposed SVM and previous ANN model [19]

Methods	Acc (%) Training	Testing
SVM	100.0	100.0
ANN [19]	100.0	88.9

3.3. IQ level prediction from perceptual ability dataset using the established model

The newly developed classification model is the used to predict IQ level from the perceptual ability dataset. Sixty-five samples of theta, alpha and beta ratio features are used as input to SVM. Seven samples are predicted as low IQ, forty-four samples as medium IQ, and the remaining fourteen samples as high IQ. Figure 2 shows the distribution of predicted IQ levels from the perceptual ability dataset. Subsequently, Table 4 shows a mapping of predicted IQ level for each perceptual ability group. All seven samples from low perceptual ability group are predicted as low IQ, and all thirteen samples from high perceptual ability group as high IQ. Meanwhile, out of forty-five samples from medium perceptual ability group, forty-four has been predicted as medium IQ. The remaining one sample is predicted as high IQ. This however, is acceptable as the sample borders the hyperplane separating between the low and high IQ groups. The IQ prediction by SVM model confirms the hypothesis that both perceptual ability and IQ levels are positively correlated. These have been established in the preceding observations on theta, alpha and beta ratio pattern, highlighting the association between these two traits of cognition through the mechanism which regulates attention. Furthermore, the model was indeed established based on the EEG pattern observed in the IQ level dataset. The similar pattern of feature distribution in perceptual ability dataset enables the model to identify the traits and predict the samples into the respective IQ level. Figure 3 further highlights the distribution of samples according to low, medium and high perceptual ability groups.

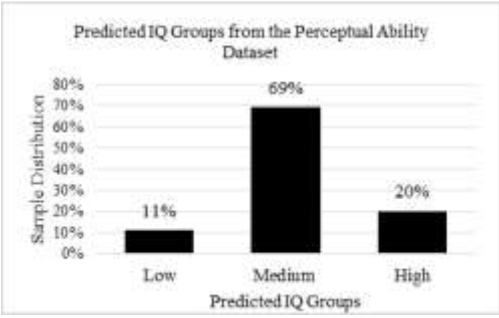
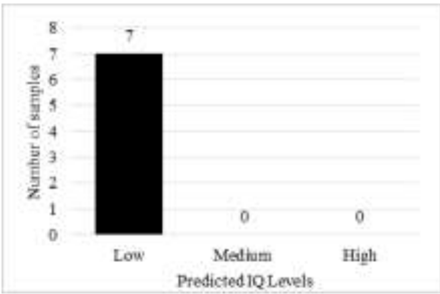


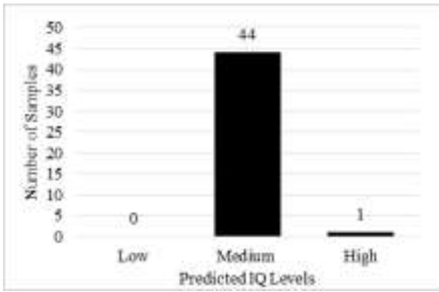
Figure 2. Distribution of predicted IQ levels from perceptual ability dataset (N=65 samples)

Table 4. Mapping of samples from perceptual ability dataset to the predicted IQ levels

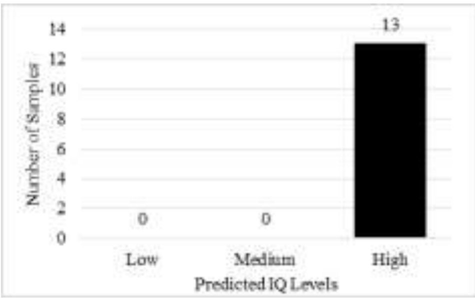
		Perceptual Ability Group			
		Low	Medium	High	Total
Predicted IQ Level	Low	7			7
	Medium		44		44
	High		1	13	14
	Total	7	45	13	65



(a)



(b)



(c)

Figure 3. Distribution of samples according to (a) low, (b) medium, and (c) high level of perceptual ability

4. CONCLUSION

This paper presents IQ level prediction and cross-relational analysis with perceptual ability using EEG-based SVM classification model. The study first sets out to characterize mean pattern of theta, alpha and beta ratio features for different levels of perceptual ability. Positive correlation between mean alpha ratio and increased level of perception has been observed. The pattern however, is inversed for mean theta and beta ratio. These are valid as it can be explained through the underlying mechanisms that regulate attention. Furthermore, it also shows strong correlation with neural transmission error and alpha suppression theories which explains increased level of attention. Similar pattern has been previously observed with IQ level dataset; indicating positive correlation between these two traits of cognition. Following the analysis on mean power ratio features and correlation between perceptual ability and IQ level, the study has successfully developed an IQ level classification model using SVM. The RBF kernel has been tuned through γ and C, yielding 100% accuracy for both training and testing. Results show marked improvement over the preceding model that was established via ANN.

Lastly, the newly developed classification model is used to predict IQ level from the perceptual ability dataset. All of the samples from low perceptual ability group have been predicted as low IQ, and all samples from the high perceptual ability group as high IQ. Meanwhile, forty-four out of forty-five samples from medium perceptual ability group has been predicted as medium IQ. The results have proven significant as the improved model has predicted IQ levels with 98.5% accuracy of the hypothesized relationship between both traits of cognition. These further validate reliability of the model for practical implementations.

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